EEG-Based Familiar and Unfamiliar Face Classification Using Differential Entropy Feature

Guoyang Liu
School of Microelectronics
Shandong University
Jinan, China
virter1995@outlook.com

Di Zhang
School of Microelectronics
Shandong University
Jinan, China
sduzhangdi@yeah.net

Lan Tian
School of Microelectronics
Shandong University
Jinan, China
tianlan65@sdu.edu.cn

Weidong Zhou*
School of Microelectronics
Shandong University
Jinan, China
wdzhou@sdu.edu.cn

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***Abstract*—This study presents a novel approach for familiar and unfamiliar face classification based on electroencephalography (EEG). Firstly, the raw EEG epoch is temporally split into three overlapped segments, and each segment is decomposed into multiple sub-bands by band-pass filters. Then, differential entropy is employed to extract discriminative EEG features. Finally, the obtained features are concatenated and classified with the support vector machine (SVM). The results yielded on our database indicate that the proposed method can achieve a mean accuracy of 76.2% over five participants. This work primarily demonstrates that differential entropy is an effective feature for EEG-based familiar and unfamiliar face classification, and has the potential to be applied to other EEG-based visual task analyses.**

Keywords—familiar and unfamiliar face classification, electroencephalography (EEG), differential entropy, brain computer interface (BCI), feature extraction

I. INTRODUCTION

Familiar and unfamiliar face recognition, an essential part of our daily lives, is closely related to social interaction. When meeting with familiar people and strangers, people might exhibit different behaviors in terms of facial expression, greetings, and specific body gestures. However, people may deliberately pretend to recognize or not recognize someone for their own benefit in some circumstances. For example, a criminal suspect usually denies familiarity to the victim to avoid being charged, or scammers commit fraud by pretending to recognize the friends and relatives of the victim. Therefore, the objective classification of the familiar and unfamiliar faces can contribute to crime investigation, lie detection, mental illness analysis, etc.

EEG as an effective tool has been widely used for monitoring and analyzing brain activities. Since previous studies suggested that the neural mechanisms corresponding to familiar and unfamiliar face recognition are quite different [1, 2], EEG is motivated to be utilized for face recognition in this study. Previous studies have preliminarily explored the feasibility of face recognition using EEG. Sun et al. [3] researched the Event-related Potential (ERP) feature of the face identification task and showed that the N400f appeared to be associated with the face classification task. Çelik et al. [4] analyzed the evoked potential in the face recognition task using wavelet features and Fisher's linear classifier, yielding a mean accuracy of 69.7%. Özbeyaz et al. [5] conducted the channel selection on EEG related to face identification, and 72.67% accuracy was obtained on Monte-Carlo cross-validation. A more recent study recorded the EEG with auditory and visual stimuli corresponding to familiar and unfamiliar people and analyzed it by functional network and complexity features [6].

Previous psychological research indicated that the emotional response to a familiar face was also an essential component of successful face recognition [7]. Therefore, unlike the short stimulus period adopted in most evoked paradigms of previous person identification experiments for detecting ERP features, in this study, we are motivated to utilize a longer visual stimulus period that is similar to the motor imagery task [8] to capture emotional-related spontaneous EEG characteristics. Meanwhile, we use the differential entropy feature that has been proved to be effective in EEG-based emotion recognition [9] to perform EEG feature extraction. Additionally, a multi-segment method in the time-frequency domain is introduced for performance improvement, and the SVM with a Gaussian kernel is employed to classify features.

II. MATERIALS AND METHODS

A. EEG Database

As listed in Table I, five healthy volunteers (aged between 18 and 25) were selected to participate in this study. Before the study, we collected 378 human face photos of world-famous people from the public domain of the Internet as the familiar face dataset, and obtained 1000 face photos generated by the StyleGAN2 model [10] from http://www.thispersondoesnotexist.com, as unfamiliar face dataset. All the photos were colorful and rescaled to square shape with a resolution of 480 pixels * 480 pixels, and each photo was checked to ensure that the face appears in the central position. Each participant was asked to delete all the unfamiliar face photos in the familiar face dataset respectively. After the image selection, 100 familiar face photos and 100 unfamiliar face photos were randomly collected from corresponding datasets, and the personalized familiar and unfamiliar face database was therefore established for each participant. The paradigm of a trial can be divided into preparation, image display, and rest stages. In the preparation stage, the screen showed the word 'Preparation' for 2-s to remind participants to concentrate on

TABLE I. DETAILED INFORMATION OF THE PARTICIPANTS

No.	Sex	Age	Trial
1	Male	25	200
2	Male	18	200
3	Female	19	200
4	Female	18	200
5	Male	18	200

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* Corresponding author

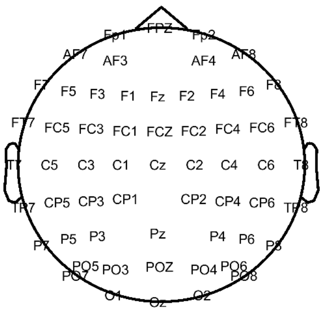

Fig. 1. The electrode placement.

the screen for the subsequent face recognition task with hands putting on their knees. Then, a randomly selected face photo was illustrated on the screen for 4-s, and the participants were asked to recall what they know about this person until the photo was disappeared. After the image displaying stage, the screen was set to a blank image with white background for 3-s representing relax period. Five block data were recorded for each participant, where each block comprised 40 continuous trials with familiar and unfamiliar face photos equally distributed. There was a short break for at least two minutes between each block, and the duration was determined by the mental state of each subject.

In this work, EEG signals were acquired with a sampling rate of 1000Hz using a NeuSen-W64 EEG data acquisition device. As shown in Fig. 1, a total of 59 electrodes were placed according to the extended 10-20 international system. The raw EEG data were resampled to 250Hz. A Leave-One-Block-Out (LOBO) cross-validation strategy was utilized to assess the proposed method, which means for each fold of validation, one block serves as the testing set while all the other blocks as the training set.

B. Proposed Method

Differential entropy is a complexity measurement of the continuous random variable. Let X be a random variable obeying Gaussian distribution $N(\mu,\sigma^2)$, and then the differential entropy can be expressed as:

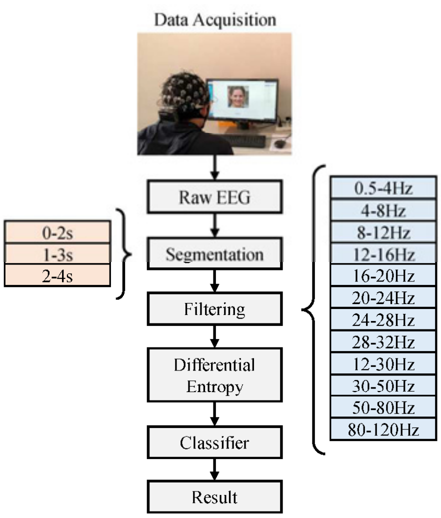

Fig. 2. The flowchart of the proposed EEG-based familiar and unfamiliar face classification task.

$$
\begin{aligned}
h(X) &= -\int_X f(x)\log_2\left(f(x)\right)dx \\
&= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log_2\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) \\
&= \frac{1}{2}\log_2(2\pi e\sigma^2)
\end{aligned}
$$

(1)

where $f(x)$ is a probability density function. To validate if the segmented and filtered EEG recordings in the face classification task are subject to the normal distribution, we conduct the Kolmogorov-Smirnov test on over two million single-channel EEG segments at the 5% significance level. The result shows that more than 80% of the EEG segments obey normal distribution. Therefore, differential entropy can be applied to extract the EEG feature in the face classification task.

The flowchart of the proposed method is illustrated in Fig. 2. The raw EEG data from the EEG acquisition device are truncated to single-trial EEG epochs with a length of 4-s. Then the single-trial EEG epochs are further divided into three 2-s segments with 50% overlapped rectangle windows. After that, the segmented EEG data is filtered by 12 4-order Butterworth band-pass filters. It can be seen from Fig. 2 that a series of band-pass filters with a bandwidth of 4Hz is employed to delta, theta, alpha, and beta frequency bands, while band-pass filters with larger bandwidth are used for gamma and higher frequency bands. This setting is a tradeoff between computational complexity and performance. Subsequently, we compute the differential entropy of each temporally segmented and band-pass filtered EEG segment and concatenate all the features to a feature vector. Finally, the SVM with a Gaussian kernel serves as a robust classifier to classify the obtained features vector and output the final decision.

III. Results and Discussion

With the aim of obtaining optimal performance, seven classifiers, including SVM with Gaussian kernel, SVM with linear kernel, linear discriminant analysis (LDA), k-nearest neighbor (kNN), Adaboost, decision tree, and naïve bayes model, are employed to classify the differential entropy features. Table II presents the LOBO cross-validation results using different classifiers. It can be observed that the SVM with Gaussian kernel outperforms other classifiers with a mean accuracy of 76.2%. The performance of the subjects on familiar and unfamiliar face classification tasks varied widely, where Subject 1 can achieve the best accuracy of 90% while Subject 5 yields the lowest accuracy. Meanwhile, for Subjects 2 and 3, the SVM with linear kernel and LDA has a higher accuracy, which indicates that the classifier can be further optimized for performance improvement. The block-based results for SVM with Gaussian kernel are illustrated in Table III. We can see that even in the same person, there exists a high variance between each block. This may be caused by the mental state change of the subject. For all participants, at least one block has an accuracy rate of 80% and above. Fig. 3 shows the detailed confusion matrix of each subject. An interesting phenomenon can be observed that the sensitivity of recognizing the familiar face is significantly lower than that of recognizing the unfamiliar face for Subjects 2, 3, and 4, while the sensitivity of the two classes is nearly the same for Subjects 1 and 5. The results

TABLE II. EXPERIMENTAL RESULTS ON VARIOUS CLASSIFIERS. THE HIGHEST MEAN ACCURACY OF EACH SUBJECT IS MARKED IN BOLDFACE.

Subject	SVM (Gaussian)	SVM (Linear)	LDA	kNN	AdaBoost	Tree	NaiveBayes
1	**90.00%**	88.50%	**90.00%**	81.50%	87.50%	87.50%	86.00%
2	80.00%	**81.00%**	78.50%	69.00%	68.50%	67.00%	70.50%
3	74.00%	78.50%	**79.00%**	68.50%	56.50%	56.00%	69.50%
4	**70.00%**	67.00%	66.50%	64.00%	63.00%	55.50%	66.00%
5	**67.00%**	57.00%	56.50%	57.00%	61.00%	56.00%	62.00%
Mean ±SD	**76.20% ±9.12%**	74.40% ±12.42%	74.10% ±12.88%	68.00% ±8.95%	67.30% ±12.09%	64.40% ±13.79%	70.80% ±9.13%

SD, Standard Deviation.

TABLE III. DETAILED EXPERIMENTAL RESULTS OF SVM WITH GAUSSIAN KERNEL.

Subject	Block 1	Block 2	Block 3	Block 4	Block 5	Max	Mean±SD
1	92.50%	95.00%	82.50%	95.00%	85.00%	95.00%	90.00%±5.86%
2	80.00%	87.50%	75.00%	75.00%	82.50%	87.50%	80.00%±5.30%
3	82.50%	80.00%	77.50%	72.50%	57.50%	82.50%	74.00%±9.94%
4	67.50%	60.00%	80.00%	67.50%	75.00%	80.00%	70.00%±7.71%
5	85.00%	80.00%	55.00%	52.50%	62.50%	85.00%	67.00%±14.73%

SD, Standard Deviation.

indicate that the familiar and unfamiliar face can stimulate different EEG patterns which can be analyzed by using the differential entropy.

IV. CONCLUSIONS

This study primarily demonstrates a novel method and paradigm for EEG-based familiar and unfamiliar face classification. The LOBO cross-validation is conducted to evaluate the performance and generalization ability of the proposed method. The experimental results indicate that the differential entropy feature combining with Gaussian SVM achieves the best performance on the face classification task. In our future work, we will employ more EEG data to verify the proposed method and evaluate its cross-subject performance. Moreover, other emotion-related EEG features will be assessed and compared, and new segmentation strategies in time and frequency domaines will be further investigated.

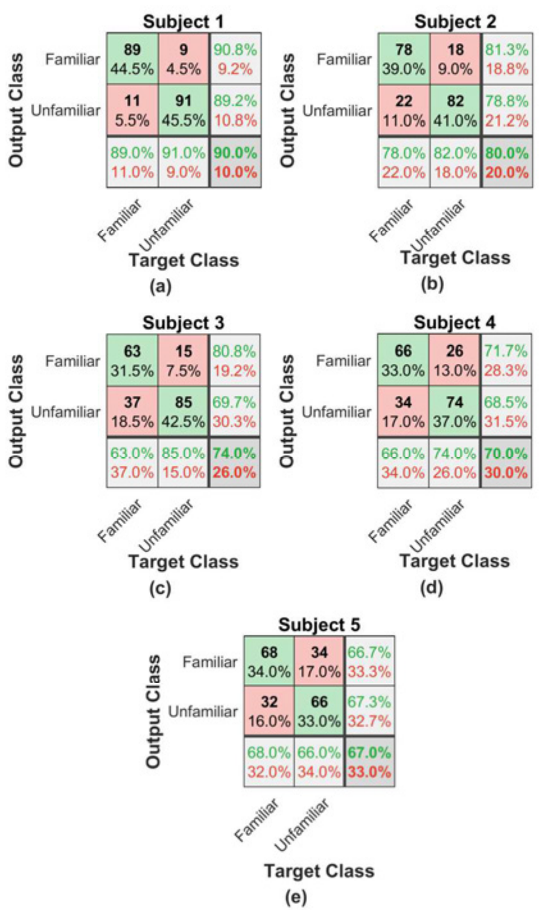

Fig. 3. The confusion matrices for five subjects.

REFERENCES

[1] M. P. Ewbank and T. J. Andrews, "Differential sensitivity for viewpoint between familiar and unfamiliar faces in human visual cortex," Neuroimage, vol. 40, no. 4, pp. 1857-1870, 2008.

[2] G. Gainotti, "Laterality effects in normal subjects' recognition of familiar faces, voices and names. Perceptual and representational components," Neuropsychologia, vol. 51, no. 7, pp. 1151-1160, 2013.

[3] D. Sun, C. C. Chan, and T. M. Lee, "Identification and classification of facial familiarity in directed lying: an ERP study," PloS one, vol. 7, no. 2, p. e31250, 2012.

[4] U. Çelik and S. Arıca, "Classification of evoked potentials of familiar and unfamiliar face stimuli using multi-resolution approximation based on excitatory post-synaptic potential waveform," Computers & Electrical Engineering, vol. 39, no. 5, pp. 1571-1584, 2013.

[5] A. Özbeyaz and S. Arica, "Classification of EEG signals of familiar and unfamiliar face stimuli exploiting most discriminative channels," Turkish Journal of Electrical Engineering & Computer Sciences, vol. 25, no. 4, pp. 3342-3354, 2017.

[6] W. Chang, H. Wang, G. Yan, and C. Liu, "An EEG based familiar and unfamiliar person identification and classification system using feature extraction and directed functional brain network," Expert Systems with Applications, vol. 158, p. 113448, 2020.

[7] M. I. Gobbini and J. V. Haxby, "Neural systems for recognition of familiar faces," Neuropsychologia, vol. 45, no. 1, pp. 32-41, 2007.

[8] Z. Y. Chin, K. K. Ang, C. Wang, C. Guan, and H. Zhang, "Multi-class filter bank common spatial pattern for four-class motor imagery BCI," in 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2009, pp. 571-574: IEEE.

[9] R.-N. Duan, J.-Y. Zhu, and B.-L. Lu, "Differential entropy feature for EEG-based emotion classification," in 2013 6th International IEEE/EMBS Conference on Neural Engineering (NER), 2013, pp. 81-84: IEEE.

[10] T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, and T. Aila, "Analyzing and improving the image quality of stylegan," in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 2020, pp. 8110-8119.